Science of the Total Environment 650 (2019) 224–232

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Climatic burden of eating at home against away-from-home: A novel Bayesian Belief Network model for the mechanism of eating-out in urban China

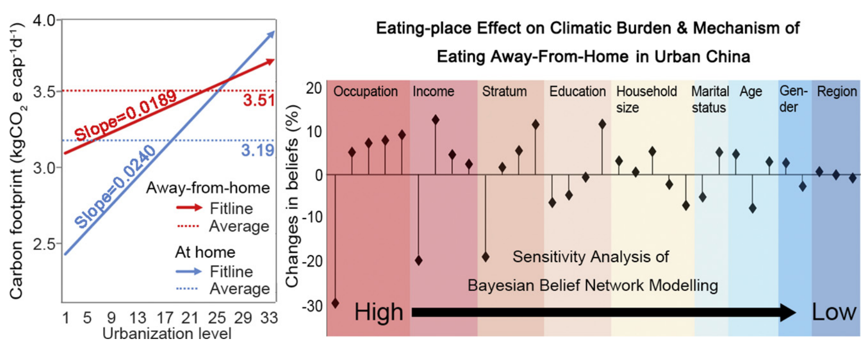
Jiaojiao Li [a], Guobao Song [a,*], Henry Musoke Semakula [a,b], Shushen Zhang [a]

[a] Key Laboratory of Industrial Ecology and Environmental Engineering (MOE), School of Environmental Science and Technology, Dalian University of Technology, Dalian 116024, China
[b] College of Agricultural and Environmental Sciences, Makerere University, Kampala 256, Uganda

HIGHLIGHTS

- The Chinese eat less food AFH than at home but generate more carbon footprint.
- Climatic burden increases more rapidly with intake of animal products at home.
- The BBN model is robust at revealing the non-linear mechanism under eating AFH.
- Occupation and income rank the top two determinants on why eating out.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 20 July 2018
Received in revised form 1 September 2018
Accepted 2 September 2018
Available online 4 September 2018

Editor: D. Barcelo

Keywords:
Eat away-from-home
Carbon footprint
Climate change
Urbanization
Socioeconomic transitioning
Bayesian Belief Network

ABSTRACT

Dietary patterns of eating away-from-home (AFH) considerably differ from those of eating at home in urban China, thus generating varied carbon footprints. However, few studies have investigated the effect of eating places on diet-related climatic burden, and few have modelled the mechanism under the condition of eating-out because the decision of consumers on whether to eat AFH or at home is determined by multiple non-linear socioeconomic factors. Here, we compared the carbon footprints of eating at home and AFH using household survey data from 12 Chinese provinces, and developed a Bayesian Belief Network (BBN) model to identify key factors of eating AFH. Our findings show that eating AFH leads to higher climatic burdens though respondents consume less food on average than when eating at home. However, in urban areas, the carbon footprint generated increases more rapidly from eating at-home than when eating AFH. The BBN model was found to have strong capability to predict the possibility of eating out with an accuracy of 89%. Although diet patterns and embedded carbon footprint vary considerably across provinces from northeastern to southwestern China, sufficient evidence could not be found to support the influence of geographic factors on the decision of respondents to eat AFH at large scale. Instead, individual occupation and income were found to be the two key contributors. Thus, merely estimating the carbon footprint of food consumption is currently not sufficient, but social and economic elements need to be quantitatively considered to differentiate the eating-place effect on diet-related climatic burden.

* Corresponding author at: 301 Office, School of Environmental Science and Technology, 2# Lingong Road, Ganjinzi District, Dalian 116024, China.
E-mail address: gb.song@dlut.edu.cn (G. Song).

https://doi.org/10.1016/j.scitotenv.2018.09.015
0048-9697/

1. Introduction

To fight against climate change, the Chinese government promised to reduce the density of greenhouse gas (GHG) emissions per unit of GDP by 60–65%, referring to the 2005 levels, by 2030 (NDRC, 2015). As one of the major source of GHG emissions, agricultural systems that supply diverse foods accounted for 18.3% of China's GHG emissions in 2013, of which meat accounted for the highest proportion of approximately 37% (Yue et al., 2017). Urbanization is the main cause of this high intake of animal products. For example, the Chinese population increased by 40% during 1970–2012, but diet-related GHG emissions almost doubled from 421 to 835 Mt. CO_2e because meat consumption significantly quadrupled (FAO, 2012). Nevertheless, Tilman and Clark (2014) approved that changing diets is conducive to reducing GHG emissions of food supply chains. For China, 5–28% of food-related carbon footprint would be reduced if age-gender specified optimal diets were adopted (Song et al., 2017, 2018).

However, only focusing on dietary changes is not enough to lower GHG emissions. This is because urbanization alters not only dietary patterns but also the eating habits of residents, such as increased frequency of restaurant visits or eating AFH (Seto and Ramankutty, 2016). Zhai et al. (2014) reported that Chinese expenditure on eating AFH increased considerably by 78–191% during 1999 to 2012, and it is difficult to stop the growth because the wealth of city dwellers continues to grow under urbanization (Liu et al., 2015). Through a recent market survey, Xiao et al. (2015) showed that eating AFH accounted for 33% of China's total meat consumption, among which urban residents are responsible for 43%, in contrast to rural counterparts at 20%. Aggravating the issue in China, eating AFH was found to account for higher consumption ruminant meat than eating at home (Xiao et al., 2015), thus generating more carbon footprint due to highly intensive methane emissions (Machovina et al., 2015; Nijdam et al., 2012). In this respect, quantitatively differentiating carbon emissions of eating AFH and at-home will aid the scientific community and policy makers to generate science-based policies for climate mitigation. However, this eating-place effect is usually neglected.

Previous reports showed that various factors are responsible for the growth of eating AFH, such as gender (Drescher and Roosen, 2013; Kim, 2016), age (Bai et al., 2016; Todd, 2017), marital status (Lee et al., 2016; Liu et al., 2013), education (Orfanos et al., 2007; Thornton et al., 2011), income (Ma et al., 2006; Min et al., 2004), occupation (Drescher and Roosen, 2013; Kim, 2016), household size (Liu et al., 2015; Liu et al., 2013; Min et al., 2004), and spatial geographic variations (Dong and Hu, 2010; Orfanos et al., 2007). Many methods were used to investigate potential associations of these socioeconomic factors with eating AFH, such as regression analysis (Adams et al., 2015; Orfanos et al., 2007), nonparametric estimation (Min et al., 2004), cohort analysis (Drescher and Roosen, 2013), Box-Cox transformed double-hurdle model (Bai et al., 2016; Liu et al., 2015), and fixed effects regression (Dong and Hu, 2010).

These methods effectively revealed the relationship between a single socioeconomic factor and eating AFH. However, nonlinear connections co-exist among all these metrics, which together affect the possibilities of consumers eating AFH. Therefore, it is necessary to adopt an integrated model that covers the causal relationship of various factors and conduct an effective reasoning analysis using previous knowledge (Laniak et al., 2013). The Bayesian Belief Network (BBN) approach is suitable for such situations because it provides a natural means of representing causal information to identify potential relationships between factors and analyse the extent to which each factor affects the output indicator. Furthermore, the Chinese territory spans across a wide distance of approximately 5500 km from north to south, which may imply varied dietary patterns and embedded carbon emissions. However, these geographical variations have not been explored.

Thus, based on the survey data of the China Health and Nutrition Survey (CHNS, 2004, 2006, 2009, and 2011), this study aims to: (Adams et al., 2015) Compare the effect of eating at home and AFH on dietary changes and related climatic burdens across 12 Chinese provinces; (Appelhans et al., 2012) develop a BBN model to quantify nonlinear effects of socioeconomic factors on eating AFH and to identify the key functional contributors.

2. Materials and methods

2.1. Definition of eating away-from-home

A universally accepted definition of eating AFH has not yet been adopted in the academic circle. Some researchers classified eating AFH according to the place where the meal is consumed (i.e., consumption place), (Kearney et al., 2001; Marín-Guerrero et al., 2008; Orfanos et al., 2007; Tian et al., 2016). Some studies adopted "prepared place" to define whether a meal belongs to eating AFH or at home (Lee et al., 2016; Orfanos et al., 2007; Vandevijvere et al., 2009; Zhai et al., 2014). For example, according to the definition based on "prepared place", an individual may have brought lunch from home but consumed at work cafeteria, and thus that meal is defined as eating AFH. In this study, we referred to the surveyed item of *V41: MEAL LOCATION* in Questionnaire 3 of CHNS and differentiated "eating AFH" and "eating at home" according to the "consumption place". Please refer to http://www.cpc.unc.edu/projects/china/data/questionnaires/C11nutr_Eng.pdf for the original questionnaire.

2.2. Quantifying urbanization

Urbanization drives dietary changes towards high consumption of animal products. However, it is difficult to quantify urbanization because it is not simply the single growth of urban population or income but the overall evolution of the socioeconomic system, thus involving multi-dimension issues. Targeting the CHNS community survey, Jones-Smith and Popkin (2010) proposed 12 community and household indicators to quantify China's urbanization process. These indicators include communications/media, population density, community diversity, economic activity, health infrastructure, housing quality, access to traditional markets, access to modern markets, social services, transportation infrastructure, education, and sanitation. For each indicator, the minimum-maximum scores were standardized within a range of 0–10, with higher scores representing high urbanization level. The urbanization index was then calculated by summing up all scores of these 12 indicators for each community, and the final score ranged from 23 to 107. Then, this urbanization index (i.e., final score) was categorized into 33 levels in an ascending order to represent the urbanization process. For each level, we quantified per capita food consumption and the related carbon footprint of eating at home and AFH.

2.3. Food intake and related carbon footprint

Food consumption data of 9 Chinese provinces and 3 municipalities of Chongqing, Beijing and Shanghai (here simplified as provinces) were downloaded from the database of China Health and Nutrition Survey (CHNS; http://www.cpc.unc.edu/projects/china/data). This study considered 1.45 million records of food consumption of 22,684 respondents from 7283 households of 294 communities in 2004, 2006, 2009, and 2011. According to Song et al. (2017), all food consumption records belonging to 1950 types were categorized into 28 groups.

For each food group, we cited the life-cycle-based carbon footprint coefficients from the Barilla Centre for Food & Nutrition (BCFN, 2014) because these coefficients are completely unavailable for most countries, including China. The BCFN database includes carbon footprint coefficients reviewed from 1237 life-cycle-assessment (LCA) studies that include five unified processes of food supply chains, including crop cultivation, breeding, industrial processes, transportation, and storage. Two functional units were available across LCA literatures of BCFN

database, i.e., gram CO_2e per litre product or gram CO_2e per gram product. The former functional unit is used for milk and vegetable oil, and the latter is for 25 other food groups. Using average densities of 1.026 g L^{-1} and 0.92 g L^{-1} for milk and vegetable oil, respectively, we converted all litre-based functional units of carbon footprint coefficients to gram-based ones, as summarized in Appendix Table A.3 of Song et al. (2017).

Although the LCA literatures reviewed by the BCFN mostly involve non-China food production systems (70% from Europe and 12% from the US), this dataset can consistently reflect the carbon footprint generation of China's food supply chains, especially in studies employing Monte Carlo simulations to quantify uncertainties. This consistency was discussed (Song et al., 2017) by comparing other studies back-to-back with the study of Li et al. (2016), which was based on Chinese local data.

Thus, a link between surveyed food consumption (with unit of g cap^{-1} d^{-1}) and LCA-based carbon footprint coefficients (unit of g CO_2e g^{-1}) was established. Across survey rounds and urbanization levels of provinces, we calculated the per capita daily consumption of each food group at home and AFH according to surveyed records and "person-days" of the CHNS dataset. More information on the quantification of per capita intakes of various food groups and related carbon footprints from the LCA perspective are available in Song et al. (2015 and 2017).

2.4. BBN model for eating AFH

Various socioeconomic factors influence restaurant visits in a non-linear and coupled manner, and the BBN model is thus suitable for identifying key factors. Based on Chen and Pollino (2012) and previous modelling experiences (Semakula et al., 2016; Song et al., 2018), we developed a BBN model following four steps: Firstly, define the purpose of the model, specify the modelling context, conceptualize the system, specify the data, and apply other prior knowledge; secondly, select model features and decide how to find model structure and parameter values; additionally, select estimation performance criteria and techniques, and identify model structure and parameters; finally, conduct conditional verification and diagnostic testing, quantify uncertainties, and evaluate model accuracy. Using the developed BBN model, key factors responsible for eating AFH by Chinese residents were identified.

2.4.1. Prior knowledge review

This study collected key correlations or explanatory variables that influence the outcome of decision (i.e., eating AFH) through literature review and experts' feedback. We searched the Web of Science using key words of "food away from home", "dine out", "eat out" and "eat away from home" and found a total of 34 literatures. Then, 14 most related literatures were purposely selected to determine the causal relationships between explanatory variables on eating-out (Table 1 and Fig. A.1).

Table 2
Parameterization of variables of the BBN model.

Node	State composition	Node	State composition
Occupation	Farmer	Education level	No education
	Service worker		Primary
	Equipment operator		Secondary
	Government official		University
	Professional	Household size (persons)	1
Income (RMB/month)	≤2000		2
	2000–5000		3
	5000–10,000		4
	≥10,000		5+
Stratum	Suburb	Marital status	Single
	Town		Married
	Urban	Age (years)	20–40
	Village		40–60
Region	Central region		≥60
	Eastern region	Gender	Male
	Western region		Female

2.4.2. BBN model structure and parameterization

Based on these surveyed variables of CHNS and related causal relationships of variables, we used Netica software (www.norsys.com, version 5.12; Norsys Software Corp., Vancouver, Canada) to structure and parameterize the BBN model. This model consists of two parts: nodes and arrow lines. Nodes represent explanatory variables and output variable. Each node's variables were discretized, parameterized, and then represented by different states (Table 2). The number of each node's status was set up to five according to the recommendation of Marcot et al. (2006) to achieve the expected precision and predicted value. The lines in the model represent the relationships between each node's variables, and the direction of an arrow indicates the direction of causality.

2.4.3. BBN model calibration and validation

Based on the CHNS database, the fields of each influence factor (i.e., node) were correlated according to the purposes of the analysis, and the aggregated data file (i.e., 10 columns of variables, and n = 589,404) was converted into a casefile in a CSV format recognized by Netica. Each row represents a record of food consumed by a respondent (over20 years) at home or AFH. The CSV source file was then randomly partitioned into two parts. The first partition was a training part (n = 471,524 accounting for 80%) used to develop the model, and the second partition test part (n = 117,880 accounting for 20%) was used to evaluate the model accuracy (Fienen and Plant, 2015). JMP software (www.jmp.com; version 10; SAS Institute, North Carolina, United States) was used to randomly generate a subset of 20% observations from the CSV source file.

Table 1
Key variables purposely selected for modelling dining out at the personal level.

Explanatory variables	Description	Sources
Occupation	Influences eating habits and meal location	(Kim, 2016)
Income (RMB/month)	Influences living standards and purchasing power	(Sun et al., 2014; Wang et al., 2015; Xie and Zhou, 2014)
Education level	Influences eating and purchasing habits	(Yang et al., 2014a; Yang et al., 2014b)
Region	Determines policies related to infrastructure development, taxation	(Xie and Zhou, 2014)
Household size (persons)	Determines cooking and eating habits	(Currier, 2008; Doherty et al., 2001; Iwata and Naoi, 2015)
Age (years)	Influences food purchase and consumption patterns and household size	(Foster, 2015)
Marital status	Influences organization of meals, their provisions and consumption	(Hawk, 2011)
Gender	Determines how food is purchased and consumed	(Mortimer and Clarke, 2011)
Stratum	Influences the demand for food and accessibility	(Satterthwaite et al., 2010)

Netica uses four criteria to examine model accuracy (Marcot et al., 2006). Firstly, a confusion matrix tests the model's ability to correctly predict both positive and negative cases of eating AFH. Based on the confusion matrix, we generated a receiver operator characteristic (ROC) curve and evaluated the prediction accuracy by successive prediction thresholds. For binary output (i.e., AFH or at home), the ROC curve represents the functional relationship between the percentage of true eating AFH (sensitivity) and the percentage of false case (1-specificity) over a range of cutoff (0.0–1.0), and each point on the curve represents the trade-off between the actual and false eating AFH predictions as the predicted thresholds increase (Pepe et al., 2006). ROC curves closer to the upper left corner of the chart indicate higher model accuracy. Additionally, the area under the ROC curve (AUC) was used to measure the quality of the model, with three boundary value intervals (0.5–0.7, 0.7–0.9, greater than 0.9) indicating model accuracies of "not very accurate" "more accurate" and "very accurate" (Greiner et al., 2000). Finally, the degree of the belief of the BBN model coinciding with values in the casefile was determined according to the metrics of error rate, scoring rules of logarithmic loss, quadratic loss, and spherical payoff. For logarithmic loss range (0–infinity) and quadratic loss range (0–2), scores close to zero represent a better model; for spherical payoff (0–1), scores closer to 1 indicate better model performance (Norsys Software Corporation, 2018).

3. Results and discussions

3.1. Inter-annual carbon footprint

From 2004 to 2011, the average per capita consumption of Chinese residents eating at home (AFH) increased slightly from 1053 (923) g cap^{-1} d^{-1} to 1100 (953) g cap^{-1} d^{-1}, and the corresponding CF grew from 3063 (3293) to 3365 (3513) g CO_2e cap^{-1} d^{-1}. Dietary patterns of eating at home (AFH) are consistently dominated by vegetal foods, among which vegetables and rice together account for 53% (41%) of total intakes and are responsible for 42% (27%) of total carbon footprint generations. In contrast, pork and beef together share only 6.5% and 9.4% of total intakes at home and AFH, respectively; but they generate 18% (27%) of total carbon footprint (Fig. 1). It is worth noting that the climatic burden of beef and lamb consumptions all decreased by 21% and 70%, respectively, during 2009–2011. This is likely attributable to the 2008 economic crisis that led to soaring ruminant prices, and

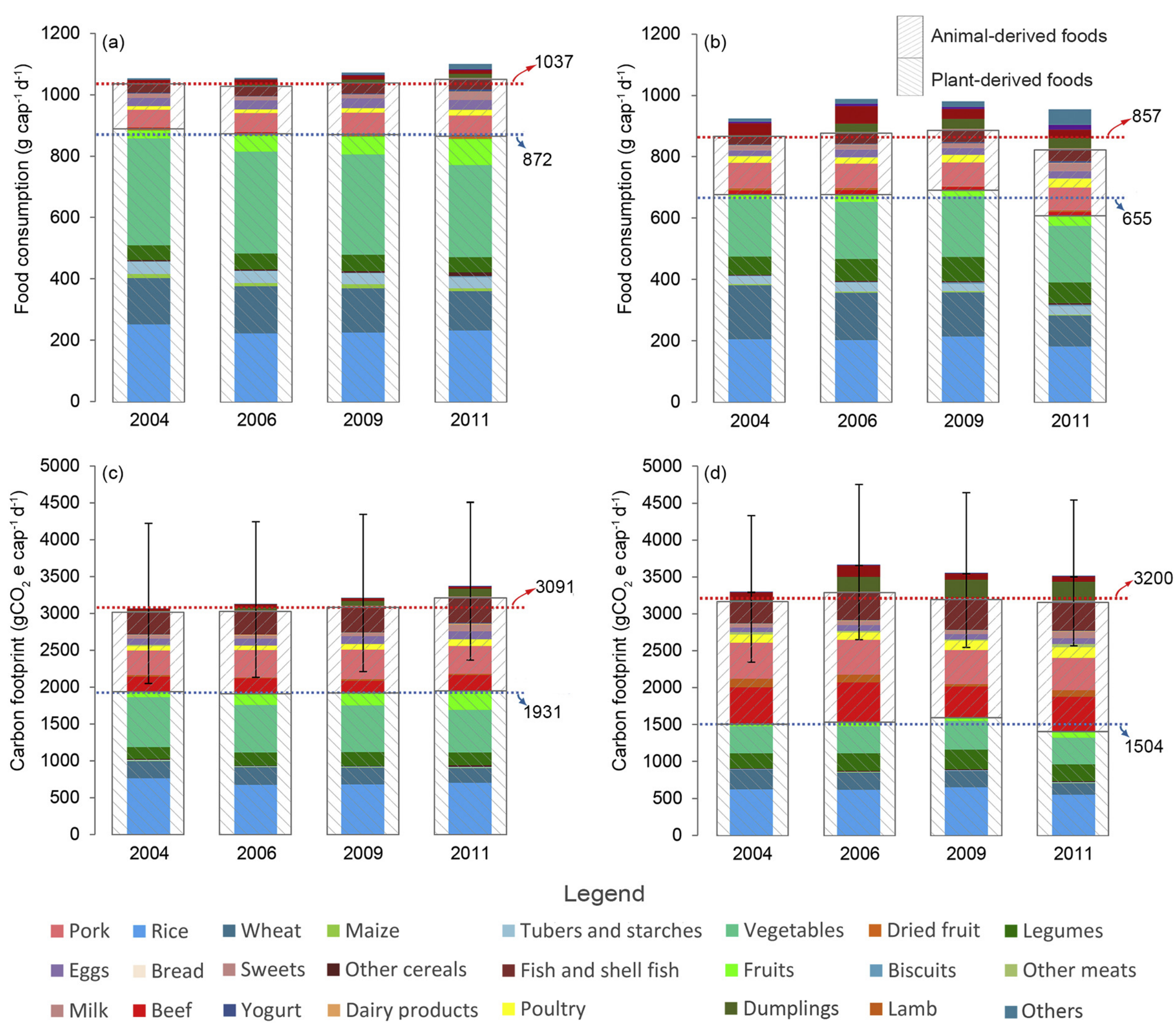


Fig. 1. Food consumption at home (a) and away from home (b), and the embedded carbon footprints in (c) and (d), respectively. The height of the blue dashed line represents the average gram or equivalent carbon dioxide of plant-derived food, and the difference between the blue and red dashed lines represent those of animal-derived food.

many Chinese families were forced to cut down their expenditure on animal products and restaurant visits (Borowy, 2008; Lee et al., 2016).

3.2. Inter-provincial carbon footprint

Across provinces from northeastern to southwestern China, Fig. 2 shows that the per capita daily consumption of eating at home (AFH) is 1168–1188 (852–1101) g cap^{-1}, generating a carbon footprint of 3955–4443 (3479–4083) g CO_2e cap^{-1} d^{-1}. The proportion of meat consumption ranges from 31 to 20% (31–25%), accounting for 45–57% (51–63%) of total carbon footprint. The average per capita carbon footprint of eating at home (AFH) is 3191 (3505) g CO_2e cap^{-1} d^{-1}, i.e., which is much lower than the Finnish average household food consumption (4700 g CO_2e cap^{-1} d^{-1}; Virtanen et al., 2011). The average intake of animal products for eating at home (AFH) is 165 (202) g cap^{-1} d^{-1}. Correspondingly, AFH eating generates more carbon footprint from animal products at 1696 g CO_2e cap^{-1} d^{-1} on average (i.e., 53%) compared with that of eating at-home at 1160 g CO_2e cap^{-1} d^{-1} (i.e., 38%).

Climate and geography influence diet patterns. For example, respondents of Heilongjiang were observed to have the least vegetable consumption at home (254 g cap^{-1} d^{-1}), whereas their intakes of poultry (31 g cap^{-1} d^{-1}) and fish (80 g cap^{-1} d^{-1}) are the highest. This is because Heilongjiang is located in the northernmost part of China, with the coldest weather (i.e., the annual average temperature of about 2.5 °C in 2009, 2010, and 2013; Gao et al., 2018). The low temperature necessitates local residents to consume more meat to keep themselves warm, and the cold weather is also unconducive to local vegetable production. Furthermore, high cost of transport and storage discourages retailers from importing vegetables from other provinces. However, fruit imports are more attractive because of higher profits. Therefore, consumers of Heilongjiang have the least vegetable intakes at-home, but higher fruit intakes (93 g cap^{-1} d^{-1}) than most surveyed provinces.

The economy also considerably influences meat intakes. For example, respondents of China's capital Beijing consume 262 g cap^{-1} d^{-1} of meat at home, which is approximately three times the consumption by residents of Guizhou province (i.e., 88 g cap^{-1} d^{-1}). This may be

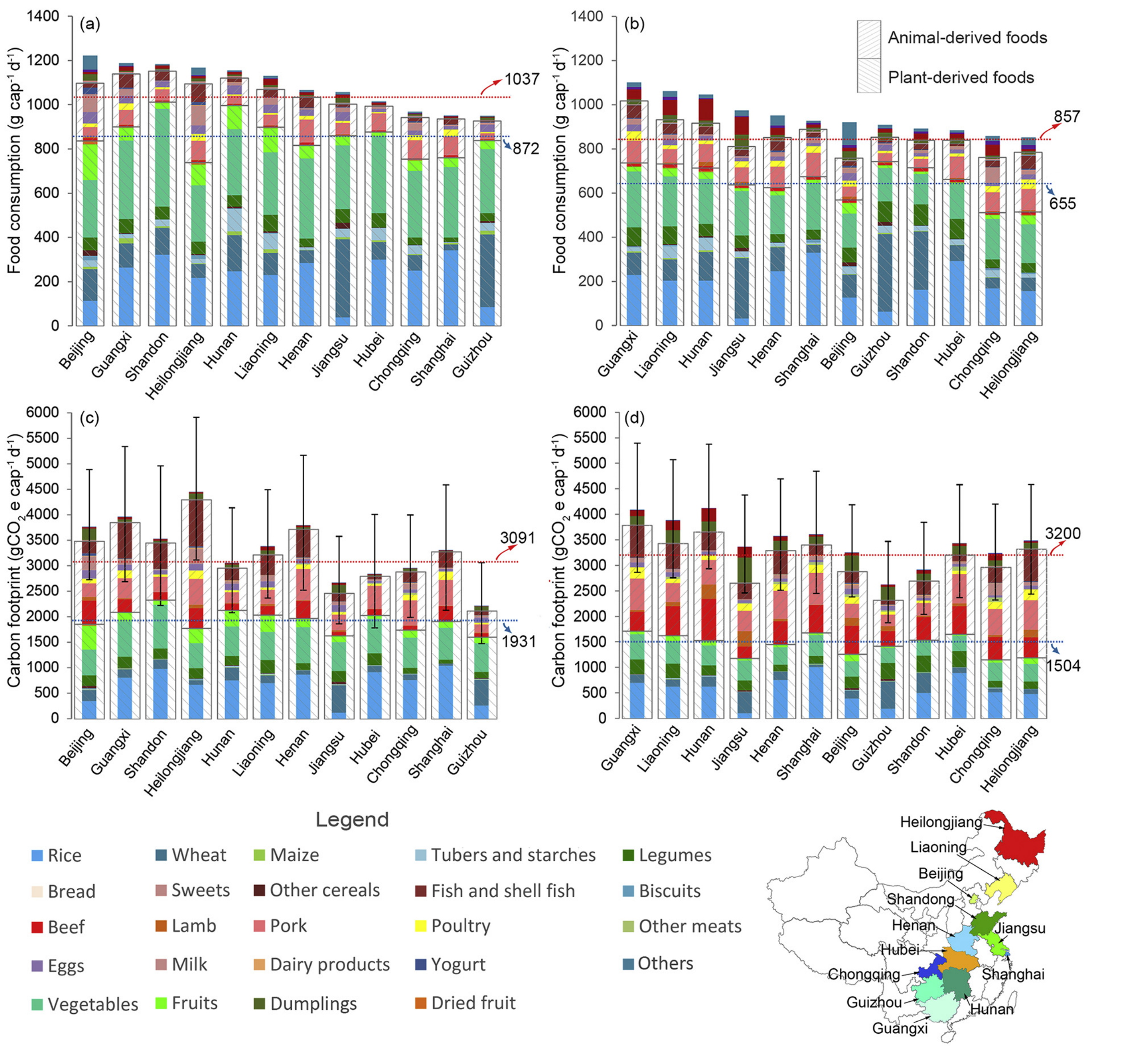


Fig. 2. Food consumption at home (a) and away from home in (b) 12 northeastern–southwestern provinces of China, with the embedded carbon footprint in (c) and (d), respectively. The height of the blue dashed line represents the average gram or equivalent carbon dioxide of vegetal intakes, and the difference between the blue and red dashed lines represents those of animal product consumptions.

attributed to the lower economic status of Guizhou where Karst topography challenges local development (Yan and Cai, 2013). Low total intakes of animal products in eating at home and AFH together contribute to Guizhou generating the least carbon footprints.

Notably, the percentage of beef consumed at home is 0.2–1.0%, accounting for 2.7–12% of carbon footprint; in contrast, eating out involves higher beef consumption (i.e., 0.7–2.1%), and thus, contributes more to carbon footprint generation (i.e., 7–20%). Moreover, respondents consume less alcohol and beverages (14 g cap^{-1} d^{-1} on average) when eating at home than when eating AFH (47 g cap^{-1} d^{-1} on average). This is mainly because alcohol and beverages are an inseparable part of Chinese social culture. Additionally, the average dairy intakes of China is 16.7 kg cap^{-1} yr^{-1}, which is much less than that of developed countries, such as America (i.e., 264 kg cap^{-1} yr^{-1}) and even much less than the world average of 83 kg cap^{-1} yr^{-1} (Wang and Li, 2008). Thus, the China Food and Nutrition Development Program has proposed to increase per capita dairy consumption up to 36 kg cap^{-1} yr^{-1} by 2020 (GOSC PRC, 2014), which will surely increase future burden on climatic change.

The effect of eating place on the intake of vegetal food and animal products varies across economies. Thus, we calculated the A/P ratio (equal to the consumption ratio of animal product to vegetal food) of 13 countries for comparative analysis (Fig. 3).

Unlike Belgium, Denmark, Norway, France, and Sweden, all surveyed Chinese provinces have higher A/P ratio of eating AFH than eating at home. Among them, Heilongjiang has the highest ratio, similar to situations in Brazil and Greece (Orfanos et al., 2007). Beijing has almost equal *A*/*P* ratios of eating at home and AFH, implying similar dietary patterns at different places. Additionally, compared with developed countries, most Chinese provinces have lower *A*/*P* ratios both at home and AFH. This implies that the shifting diet in China towards high consumption of animal products cannot be easily changed under urbanization, although the benefit of healthy diets to mitigate climate change is attractive (Song et al., 2017, 2019).

3.3. Carbon footprint growth under urbanization

Urbanization is known to drive dietary changes. However, the relative roles of animal products and vegetal foods in affecting carbon emissions through dietary patterns of eating at home and AFH have not been clarified quantitatively. For each urbanization level among 1–33 (Section 2.1), we calculated the carbon footprint ratio of animal product to vegetal food (Fig. 4).

The carbon footprint of daily food consumption at home (AFH) increases by 74% (53%) from 2235 (2433) CO_2e cap^{-1} at the first urbanization level to 3899 (3725) CO_2e cap^{-1} at the highest urbanization level. Irrespective of eating at-home or outside, animal-products (orange bars) become more important in carbon emission along with urbanization. However, the carbon footprint of meat consumption at home increases more rapidly than that AFH, as reflected by the steeper slope of fitted lines from the initial value of 0.0240 (Fig. 4a) to the final of 0.0189 (Fig. 4b). It is noteworthy that this observation does not mean the insignificance of eating AFH in increasing climatic burdens. Instead, the carbon footprint ratios of most urbanization levels (i.e., 18 out of 33 levels) are more than 1.0 for eating AFH (Fig. 4b); in contrast, only one carbon footprint ratio more than 1.0 was observed for eating at home with the urbanization index of 93–95 (Fig. 4a). This result implies that frequent visits to restaurants invariably increase carbon emission due to high meat intakes.

3.4. BBN model performance

Based on these reviewed connections among purposely selected key variables (Table 1), we developed the BBN model to predict the possibility of eating AFH (Fig. 5). Results show that the average possibility of Chinese adults eating AFH is 11.3%, according to interviewee responses of the CHNS database in 2004, 2006, 2009, and 2011.

A confusion matrix showed that the error rate of this BBN model is 10.18% (Table A1) indicating an accuracy as 89.82%. Moreover, the results of scoring rule show a strong predictive power with both the logarithmic loss (0.28) and quadratic loss (0.17) scores close to zero, and spherical payoff (0.91) approaching 1. Additionally, the ROC curve (Fig. A.2) suggests that the model performs better than a random-guessing model that carries no classifier information (Marcot, 2012). Finally, the model's AUC value is 0.76, which is higher than that of the random-guessing model (AU = 0.50), implying that the model's ability to distinguish between eating at home and AFH is much better than a random-guessing model. Based on the grading levels of the BBN model (Alpha, Beta, and Gamma; Marcot et al., 2006), the BBN model of this study can be classified as Gamma-level.

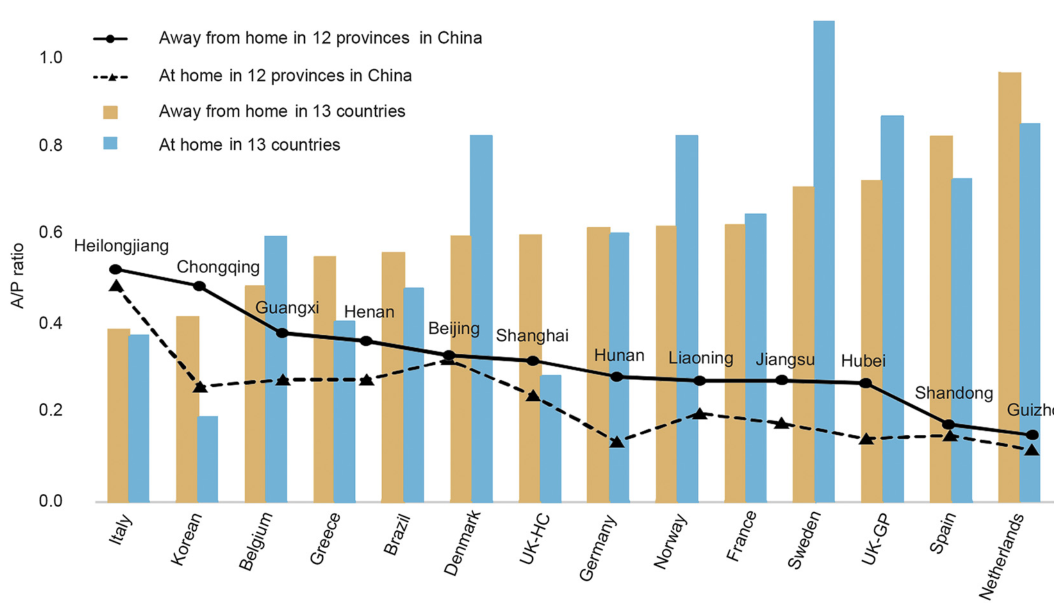


Fig. 3. Comparison of the consumption ratio of animal products to vegetable foods (A/P ratio) across Chinese provinces and other countries, with data from previous studies. GP-general populations, HC-health conscious. (Cunha et al., 2018; Lee et al., 2016; Orfanos et al., 2007; Vandevijvere et al., 2009).

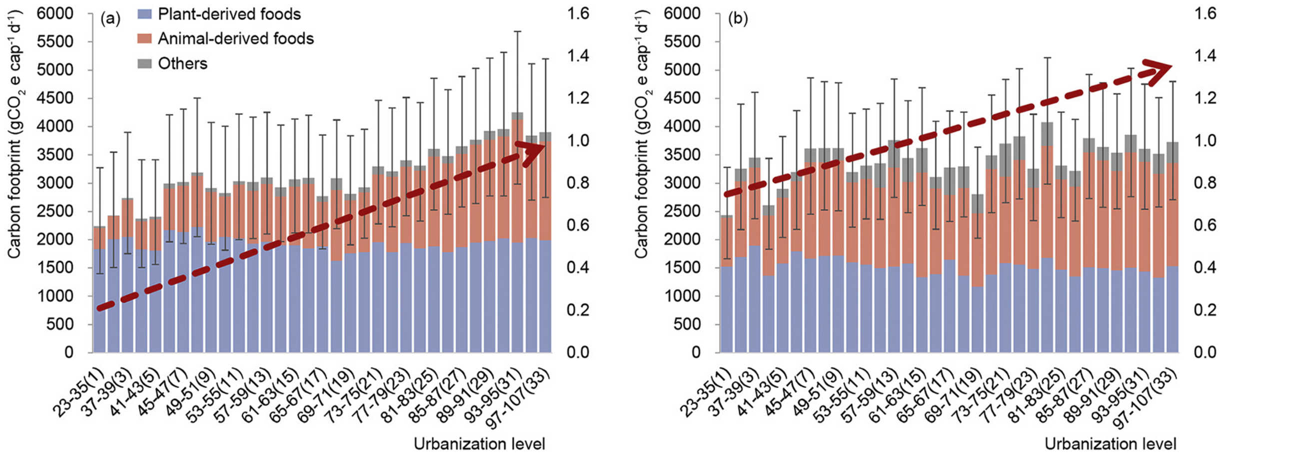


Fig. 4. Carbon footprint of food consumption against China's urbanization level. Uncertainties represent 95% confidence intervals based on Monte Carlo simulations. The ranges of the X-axis represent urbanization indexes summing the twelve dimensional components, with values of 1–33 in brackets indicating categorized urbanization levels. (a) Carbon footprint of eating at home, with the dashed red line as the fitness of the carbon footprint ratio of animal products to vegetal food, i.e., A/F, ($y = 0.0240x + 0.19$, Adj-$R^2 = 0.90$); and (b) away from home against urbanization levels with linear fitness ($y = 0.0189x + 0.73$, Adj-$R^2 = 0.62$).

3.4.1. Sensitivity analysis

Multiple variables interacting with each other contribute to the possibility of eating AFH in a nonlinear manner, as modelled in Fig. 5. To identify the key contributors to outside eating, we conducted a sensitivity analysis. Fig. 6 shows results of predicted changes of all explanatory variables when assuming absolute eating AFH. Changes in beliefs (CIB) were used to calculate the percentage differences for each independent variable to express the prediction of eating AFH. Explanatory variable nodes were ranked in a color series from red to blue according to their degrees of influencing the output of target nodes (See Table A2 for detailed entropy reduction values). A positive percentage indicates high probability of eating AFH, while a negative percentage indicates low probability.

The sensitivity analysis suggests that occupation and income are the two most important indicators affecting residents' eating AFH, followed by urbanization stratum, education, and family size. Gender appeared to have the least impact (Fig. 6). Our results of the BBN model are consistent with most previous reports from developed economies. For example, well-educated individuals with high income are more likely to choose eating AFH according to investigations from the United States (Liu et al., 2013), Korea (Lee et al., 2016), and Europe (Orfanos et al., 2007). Although provincial differences led to considerable differences in dietary patterns across Chinese provinces (Fig. 2), the macro-scale factor (regional variations) ranked the last according to the degree of influencing consumer decision of eating AFH.

For occupation, professional and technical individuals are more likely to eat AFH (CIB: +9.26%), whereas farmers have the lowest probability (CIB: −29.8%). Considering income factors, the probability of eating AFH is the least (CIB: −19.96%) if the monthly income of an individual is less than 2000 RMB (equivalent 300 USD). Wealth growth increases the possibility of eating out, but not continuously. For example, residents with monthly incomes ranging 2000–5000 RMB exhibit the highest likelihood of eating AFH, but they lose interest in frequent visits to restaurants when their income reaches over 10,000 RMB per month (Fig. 6). The results of the analysis on urbanization stratum shows that rural residents were far less likely to eat

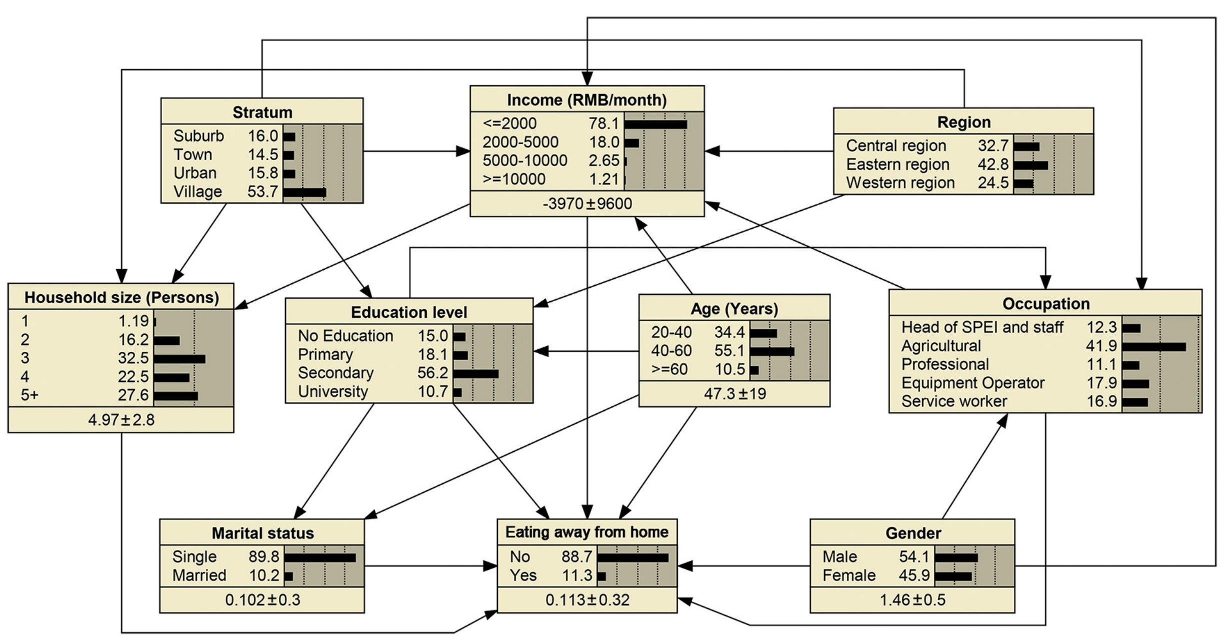


Fig. 5. Bayesian Belief Network model for the possibility of eating away from home in Chinese adults above the age of twenty years.

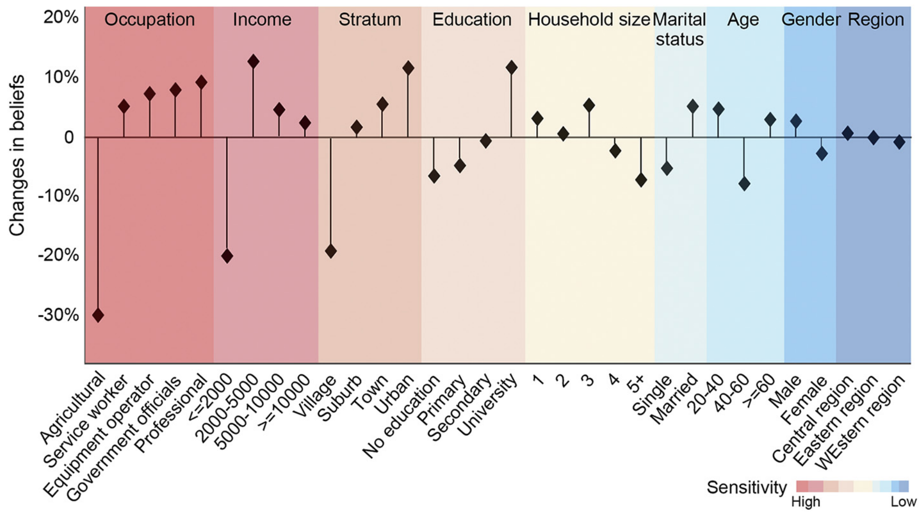


Fig. 6. Sensitivity analysis results (color series) and predicated changes in beliefs of states (the stem plots) with the target node of eating away-from-home set at 100%.

AFH (CIB: -19.10%) than their counterpart of city dwellers (CIB: +11.73%). This means that, in China, the incidence of eating out will continue with urbanization, and thus more climatic burdens are inevitable.

Highly-educated individuals (i.e., university or above) have a higher possibility of eating AFH (CIB: +11.77%), whereas less uneducated individuals show the least possibility (CBI: −6.44%). Individuals aged 20–40 show the highest probability of eating out (CIB: +4.80%), whereas adults aged 40–60 years, who face great economic pressure to support children and parents, show the least probability (CIB: −7.8%). However, elderly people over 60 years tend to eat AFH more often with a negligible positive CIB of +2.99%. This result is slightly inconsistent with that of Liu et al. (2015b), who reported that residents over 65 years show less restaurant visits. These differences are likely to occur due to variations in the sampling uncertainties of this study and previous reports. Furthermore, Lee et al. (2016) believed that singles and males tend to eat AFH more often. However, an inverse result was observed, especially for families with three members being most likely to eat out. This result was derived by combining the CBI values of “household size” and “marital status” notes in Fig. 6.

To the best of our knowledge, this is the first study on analysing the effect of eating place on climatic burdens based on massive household survey data. Furthermore, the BBN model facilitates the differentiation of the economic effect on eating AFH, although hidden linkages exist between urbanization and food systems which interact in a non-linear manner, as summarized by Seto and Ramankutty (2016).

Despite the comprehensive analysis, our study still has some limitations. Our review on socioeconomic factors of eating AFH may not cover all previous studies, and thus inadvertently ignore some influencing factors. For example, existing studies have shown the association of female impulsivity with eating AFH (Appelhans et al., 2012). This factor was not considered because the CHNS database was initially designed to examine the effects of health, nutrition, and family planning policies instead of focusing on eating AFH. Thus, although detailed records of food consumption and demographic information were very useful to quantify the generation of carbon footprint through dietary patterns, psychological factors were not included in our BBN model due to limited data of CHNS. Additionally, the CHNS surveys in 2004, 2006, 2009, and 2011 were conducted mostly during the period from July to December, and thus, the seasonal trend of dietary patterns could not be considered, introducing uncertainties in the results of this study (Zhang et al., 2006). The seasonal effect on eating behaviour and cooking methods (including eat AFH) are thus worthy of future in-depth investigations.

4. Conclusions

Focusing on the effects of eating-place on the climatic burden of urbanization in China, we compared the carbon footprint of eating at home and AFH. Then, we developed a BBN model to further reveal the mechanism of eating-out. The gradient of urbanization covering 33 urbanization levels was also established to quantify the effect of urbanization on the relative roles of animal products and vegetal foods in the generation of carbon footprint.

This study shows that, under the condition of urbanization, the consumption of animal products increase more rapidly at home than AFH, but residents generate more carbon footprint (per capita per day average) when eating out. Although wide variations of dietary patterns and embedded carbon footprint were observed across geographically distant provinces of China, sensitivity analysis results of the BBN model did not provide sufficient evidence to prove the influence of this macro-scale spatial factor on the decision of consumer to eat AFH. Instead, micro-scale factors of occupation, income, and education at the individual level were quantitatively identified as the key factors influencing the selection of the eating place. Differentiating the roles of eating at home and AFH in impacting climate change, this study provides a fundamental basis for investigating in detail the effect of urbanization on dietary changes and its implications for climate change.

Acknowledgments

This study is supported by the Fundamental Research Funds for the Central Universities (DUT18LAB13), and the Program of Introducing Talents of Disciplines to Universities (B13012). We thank the Barilla Center of Food & Nutrition of Italy for its great effort in reviewing and sharing the database of the Double Food-Environmental Pyramid model; and the China Health and Nutrition Survey for sharing data (http://www.cpc.unc.edu/projects/china).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.09.015.

References

Adams, J., Goffe, L., Brown, T., Lake, A.A., Summerbell, C., White, M., Wrieden, W., Adamson, A.J., 2015. Frequency and socio-demographic correlates of eating meals out and take-away meals at home: cross-sectional analysis of the UK national diet and nutrition survey, waves 1-4 (2008-12). Int. J. Behav. Nutr. Phys. Act. 12, 51.

Appelhans, B.M., Waring, M.E., Schneider, K.L., Pagoto, S.L., DeBiasse, M.A., Whited, M.C., et al., 2012. Delay discounting and intake of ready-to-eat and away-from-home foods in overweight and obese women. Appetite 59, 576–584.

Bai, J., Zhang, C., Wahl, T., Seale Jr., J., 2016. Dining out, the missing food consumption in China. Appl. Econ. Lett. 23, 1084–1087.

Barilla Center for Food & Nutrition (BCFN), 2014. DFEP The literature database of reviewed LCA studies on foods. https://www.barillacfn.com/m/publications/doublepyramid2014-data.zip (Accessed Dec 2016).

Borowy, I., 2008. Crisis as opportunity: international health work during the economic depression. Dynamis 28, 29–52.

Chen, S.H., Pollino, C.A., 2012. Good practice in Bayesian network modelling. Environ. Model. Softw. 37, 134–145.

CHNS, 2004, 2006, 2009, and 2011, d. New Development of Data Availability.Available online:. http://www.cpc.unc.edu/projects/china (accessed on February in 2013).

Cunha, D.B., Bezerra, I.N., Pereira, R.A., Sichieri, R., 2018. At-home and away-from-home dietary patterns and BMI z-scores in Brazilian adolescents. Appetite 120, 374–380.

Currier, C.L., 2008. Investing in the future: the one child policy and reform. J. Women Politics Policy 29, 365–393.

Doherty, J.P., Norton, E.C., Veney, J.E., 2001. China's one-child policy: the economic choices and consequences faced by pregnant women. Soc. Sci. Med. 52, 745–761.

Dong, X., Hu, B., 2010. Regional difference in food consumption away from home of urban residents: a panel data analysis. Agric. Agric. Sci. Procedia 1, 271–277.

Drescher, L.S., Roosen, J., 2013. A cohort analysis of food-at-home and food-away-from-home expenditures in Germany. J. Int. Agric. Trade Dev. 62, 39–51.

FAO, 2012. Food and Agriculture Organization. Statistic Database of Greenhouse Gasses Emissions From Agriculture.Available online:. http://www.fao.org/faostat/en/#data/GT (accessed on April in 2018).

Fienen, M.N., Plant, N.G., 2015. A cross-validation package driving Netica with python. Environ. Model. Softw. 63, 14–23.

Foster, A.C., 2015. Consumer expenditures vary by age. Beyond the Numbers. 4. Bureau of Labor Statistics, Washington, DC, pp. 1–11.

Gao, Z.Y., Wang, C.W., Wang, J., Hu, W.D., 2018. An analysis of air temperature evolution and its future trend in Heilongjiang province. J. Glaciol. Geocryol. 40, 270–278 (in Chinese).

General Office of the State Council of the People's Republic of China (GOSC, PRC), 2014. Available online:. http://www.nhfpc.gov.cn/jkj/s5877/201402/e0c27e00e4004aa39f3a24fbeb027fb3.shtml (accessed on January in 2018, in Chinese).

Greiner, M., Pfeiffer, D., Smith, R.D., 2000. Principles and practical application of the receiver-operating characteristic analysis for diagnostic tests. Prev. Vet. Med. 45, 23–41.

Hawk, W., 2011. Household spending by single persons and married couples in their twenties: a comparison. Consumer Expenditure Survey Anthology. Bureau of Labor Statistics, Washington, DC, pp. 40–46.

Iwata, S., Naoi, M., 2015. The asymmetric housing wealth effect on childbirth. Rev. Econ. Househ. 1–20.

Jones-Smith, J.C., Popkin, B.M., 2010. Understanding community context and adult health changes in China: development of an urbanicity scale. Soc. Sci. Med. 71, 1436–1446.

Kearney, J.M., Hulshof, K., Gibney, M.J., 2001. Eating patterns – temporal distribution, converging and diverging foods, meals eaten inside and outside of the home – implications for developing FBDG. Public Health Nutr. 4, 693–698.

Kim, G., 2016. The impact of households' characteristics on food at home and food away from home. Southern Agricultural Economics Association's 2016 Annual Meeting.

Laniak, G.F., Olchin, G., Goodall, J., Voinov, A., Hill, M., Glynn, P.W., Whelan, G., Geller, G., Quinn, N., Blind, M., Peckham, S., Reaney, S., Gaber, N., Kennedy, R., Hughes, A., 2013. Integrated environmental modeling: a vision and roadmap for the future. Environ. Model. Softw. 39, 3–23.

Lee, K.W., Song, W.O., Cho, M.S., 2016. Dietary quality differs by consumption of meals prepared at home vs. outside in Korean adults. Nutr. Res. Pract. 10, 294–304.

Li, H.M., Wu, T., Wang, X., Qi, Y., 2016. The greenhouse gas footprint of China's food system: an analysis of recent trends and future scenarios. J. Ind. Ecol. 20, 803–817.

Liu, M., Kasteridis, P., Yen, S.T., 2013. Who are consuming food away from home and where? Results from the Consumer Expenditure Surveys. Eur. Rev. Agric. Econ. 40, 191–213.

Liu, H., Wahl, T.I., Seale Jr., J.L., Bai, J., 2015. Household composition, income, and food-away-from-home expenditure in urban China. Food Policy 51, 97–103.

Ma, H., Huang, J., Fuller, F., Rozelle, S., 2006. Getting rich and eating out: consumption of food away from home in urban China. Can. J. Agric. Econ./Revue canadienne d'agroeconomie 54, 101–119.

Machovina, B., Feeley, K.J., Ripple, W.J., 2015. Biodiversity conservation: the key is reducing meat consumption. Sci. Total Environ. 536, 419–431.

Marcot, B.G., 2012. Metrics for evaluating performance and uncertainty of Bayesian network models. Ecol. Model. 230, 50–62.

Marcot, B.G., Steventon, J.D., Sutherland, G.D., Mccann, R.K., 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. Can. J. For. Res./Revue Canadienne De Recherche Forestière 36, 3063–3074.

Marín-Guerrero, A.C., Gutiérrez-Fisac, J.L., Guallar-Castillón, P., Banegas, J.R., Rodríguez-Artalejo, F., 2008. Eating behaviours and obesity in the adult population of Spain. Br. J. Nutr. 100, 1142.

Min, I., Fang, C., Li, Q., 2004. Investigation of patterns in food-away-from-home expenditure for China. China Econ. Rev. 15, 457–476.

Mortimer, G., Clarke, P., 2011. Supermarket consumers and gender differences relating to their perceived importance levels of store characteristics. J. Retail. Consum. Serv. 18, 575–585.

National Development and Reform Commission (NDRC), 2015. Enhanced Actions on Climate Change: China's Intended Nationally Determined Contributions.Available online:. http://www4.unfccc.int/Submissions/INDC/Published%20Documents/China/1/China's%20INDC%20-%20on%2030%20June%202015.pdf (accessed on Jul in 2018).

Nijdam, D., Rood, T., Westhoek, H., 2012. The price of protein: review of land use and carbon footprints from life cycle assessments of animal food products and their substitutes. Food Policy 37, 760–770.

Norsys Software Corporation, 2018. Tutorial on Bayesian Network in Netica.Available online:. www.norsys.com/tutorials/netica/secD/tut_D2.htm (accessed on Mar in 2018).

Orfanos, P., Naska, A., Trichopoulos, D., Slimani, N., Ferrari, P., van Bakel, M., et al., 2007. Eating out of home and its correlates in 10 European countries. The European Prospective Investigation into Cancer and Nutrition (EPIC) study. Public Health Nutr. 10, 1515–1525.

Pepe, M.S., Cai, T., Longton, G., 2006. Combining predictors for classification using the area under the receiver operating characteristic curve. Biometrics 62, 221–229.

Satterthwaite, D., McGranahan, G., Tacoli, C., 2010. Urbanization and its implications for food and farming. Philos. Trans. R. Soc. B Biol. Sci. 365, 2809–2820.

Semakula, H.M., Song, G., Achuu, S.P., Zhang, S., 2016. A Bayesian belief network modelling of household factors influencing the risk of malaria: a study of parasitaemia in children under five years of age in sub-Saharan Africa. Environ. Model. Softw. 75, 59–67.

Seto, K.C., Ramankutty, N., 2016. Hidden linkages between urbanization and food systems. Science 352, 943–945.

Song, G.B., Li, M., Semakula, H.M., Zhang, S., 2015. Food consumption and waste and the embedded carbon, water and ecological footprints of households in China. Sci. Total Environ. 529, 191–197.

Song, G.B., Li, M., Fullana-I-Palmer, P., Williamson, D., Wang, Y., 2017. Dietary changes to mitigate climate change and benefit public health in China. Sci. Total Environ. 577, 289–298.

Song, G.B., Semakula, H.M., Fullana-I-Palmer, P., 2018. Chinese household food waste and its climatic burden: a Bayesian Belief Network modelling for reduction possibility in the context of global efforts. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2018.08.233 Available online:.

Song, G.B., Gao, X.B., Fullana-I-Palmer, P., Lv, D.Q., Zhu, Z.C., Wang, Y.X., Bayer, L.B., 2019. Shift from feeding to sustainably nourishing urban China: a crossing-disciplinary methodology for global environment-food-health nexus. Sci. Total Environ. 647, 716–724.

Sun, W., Wang, X., Bai, C.E., 2014. Income inequality and mobility of rural households in China from 2003 to 2006. China Agr. Econ. Rev. 6, 73–91.

Thornton, L.E., Crawford, D.A., Ball, K., 2011. Who is eating where? Findings from the SocioEconomic Status and Activity in Women (SESAW) study. Public Health Nutr. 14, 523–531.

Tian, X., Zhong, L., von Cramon-Taubadel, S., Tu, H., Wang, H., 2016. Restaurants in the neighborhood, eating away from home and BMI in China. PLoS ONE 11, e0167721.

Tilman, D., Clark, M., 2014. Global diets link environmental sustainability and human health. Nature 515, 518–522.

Todd, J.E., 2017. Changes in consumption of food away from home and intakes of energy and other nutrients among US working-age adults, 2005–2014. Public Health Nutr. 20, 3238–3246.

Vandevijvere, S., Lachat, C., Kolsteren, P., Van Oyen, H., 2009. Eating out of home in Belgium: current situation and policy implications. Br. J. Nutr. 102, 921.

Virtanen, Y., Kurppa, S., Saarinen, M., Katajajuuri, J., Usva, K., Mäenpää, I., et al., 2011. Carbon footprint of food – approaches from national input–output statistics and a LCA of a food portion. J. Clean. Prod. 19, 1849–1856.

Wang, Y., Li, S., 2008. Worldwide trends in dairy production and consumption and calcium intake: is promoting consumption of dairy products a sustainable solution for inadequate calcium intake? Food Nutr. Bull. 29, 172–185.

Wang, C., Zhang, C., Ni, J., 2015. Social network, intra-network education spillover effect and rural–urban migrants' wages: evidence from China. China Econ. Rev. 35, 156–168.

Xiao, H., Chen, Q., Wang, J., Oxley, L., Ma, H., 2015. The puzzle of the missing meat: food away from home and China's meat statistics. J. Integr. Agric. 14, 1033–1044.

Xie, Y., Zhou, X., 2014. Income inequality in today's China. Proc. Natl. Acad. Sci. 111, 6928–6933.

Yan, X., Cai, Y.L., 2013. Multi-scale anthropogenic driving forces of karst rocky desertification in southwest China. Land Degrad. Dev. 26, 193–200.

Yang, J., Huang, X., Liu, X., 2014a. An analysis of education inequality in China. Int. J. Educ. Dev. 37, 2–10.

Yang, J., Sicular, T., Lai, D., 2014b. The changing determinants of high school attainment in rural China. China Econ. Rev. 30, 551–566.

Yue, Q., Xu, X., Hillier, J., Cheng, K., Pan, G., 2017. Mitigating greenhouse gas emissions in agriculture: from farm production to food consumption. J. Clean. Prod. 149, 1011–1019.

Zhai, F.Y., Du, S.F., Wang, Z.H., Zhang, J.G., Du, W.W., Popkin, B.M., 2014. Dynamics of the Chinese diet and the role of urbanicity, 1991–2011. Obes. Rev. 15, 16–26.

Zhang, X., Zhao, W., He, L., Chen, J., 2006. Study on the change trend of food consumption in one year in North and South China. J. Hyg. Res. 35, 487–488 (in Chinese).